Measuring and Accounting for Cross-Country Differences in Education Quality

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Abstract

This paper measures the role of quality-adjusted education in accounting for cross-country differences in income per worker. The returns to schooling of immigrants to the United States are used as a measure of their source-country education quality. Returns are available for 130 countries and vary by up to an order of magnitude between developed and developing countries. A model shows why the returns to schooling of immigrants and not other wage statistics are an appropriate measure of education quality. The model is consistent with the relationships between education quality, average school attainment, and the returns to schooling for immigrants and non-migrants. Calibrating the model, or augmenting a Bils and Klenow (2000)-style accounting exercise to account for education quality, yields large results. Quality-adjusted schooling is found to account for 38-42% of the income difference between the richest and poorest quintiles of countries, as opposed to the 21-24% in the current literature that accounts only for years of schooling.

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1 Introduction

Cross-country differences in PPP-adjusted output per worker are large: workers in the poorest countries in the world produce about 3% of what workers in the U.S. produce. To make progress in identifying the determinants of these large differences, the levels accounting literature attempts to decompose output per worker differences across countries into underlying differences in capital, human capital, and a residual term typically associated with technology and institutions.[1] The consensus in this literature is that schooling specifically, and human capital more broadly, are of minor importance relative to the residual term. For instance, Hall and Jones (1999) find that replacing the poorest country's human capital with U.S. levels would only raise their income from 3% to 7.5% of U.S. levels.

These inferences are based on the pioneering methodology of Bils and Klenow (2000). They collect micro-level estimates of the Mincerian (log wage) returns to schooling around the world and estimate a relationship $M(S)$ giving the marginal value M of year of schooling S. They use this evidence on the wage gains to schooling to impute the role of schooling in accounting for output gaps across countries. However, their methodology assigns the same value to the first year of schooling in, say, Sweden and Pakistan. Hence, it measures differences in quantity of schooling, but not education quality. Taking the value of a year of schooling as constant across countries is contrary to evidence from internationally standardized achievement tests that there are large education quality differences across countries.[2]

The primary difficulty in accounting for education quality is a lack of scaled data. It is hard to translate the large differences in scores on internationally standardized achievement tests into their importance for accounting for cross-country income differences. This paper introduces an alternative, scaled measure: the returns to schooling of U.S. immigrants.[3] Specifically, I construct a sample of immigrants who completed their schooling abroad, subsequently immigrated to the United States, and were active in the labor force for the 2000 U.S. Census. The measured returns vary greatly by country of education, and are highly positively correlated with countries' scores on internationally standardized achievement tests and development status. For example, a year of Somalian or Nepalese education has a

[1] See Caselli (2005) for an overview of the accounting literature.

[2] Bils and Klenow (2000) use a separate method to account for education quality, as discussed below. Since Hall and Jones (1999), it has been common in the literature to use only the years of schooling accounting as discussed here.

[3] Card and Krueger (1992) first studied returns to schooling of cross-state migrants in the U.S., while Bratsberg and Terrell (2002) used returns to schooling for immigrants. Both papers focus on estimating the education quality production function; this is the first paper to integrate this data into an accounting exercise.

return of less than 1%, while a year of Swedish or Japanese education has a return of over 10%. Further, the large number of immigrants in the U.S. makes it possible to construct estimated returns for 130 countries.

Hendricks (2002) previously used information on U.S. immigrants to estimate cross-country differences in human capital stocks. The measurement exercise here is narrower. Returns to schooling measure education quality, not the entire human capital stock. Focusing on education quality offers advantages in addressing immigrant selection. Only a particular form of differential selection biases the measurement; the paper argues that this selection story is unlikely to explain much of the results. Further, test scores offer a natural instrument for education quality, adding a second check.

The resulting measure of education quality is incorporated into two levels accounting exercises. The first exercise develops a model to motivate why returns to schooling are the right statistic to measure education quality. It also shows that the model is consistent with the observed impact of education quality on average school attainment and returns to schooling for immigrants and non-migrants. Average attainment, the returns to schooling for immigrants, and education quality proxies such as test scores are all highly positively correlated. However, the returns to schooling for non-migrants are nearly uncorrelated with each of those variables. For accounting results to be taken seriously, a model should be consistent with these facts.

Incorporating two new features into the standard accounting framework makes it consistent with these facts. First, endogenous school choice explains that workers go to school until the returns to schooling are driven down to the opportunity cost of a year of education. The opportunity cost is determined by workers' discount rates and the tuition cost of schooling relative to income, which are reasonably similar across countries. Hence, returns to schooling for non-migrants should be similar across countries as well. Workers who have access to higher quality education earn higher returns on a given year, but go to school longer until returns are equated to opportunity cost. Hence, endogenous school choice can explain the patterns between education quality, average attainment, and returns to schooling for non-migrants.

That returns to schooling for immigrants are uncorrelated with returns to schooling for non-migrants is more difficult to explain. Under the standard accounting assumptions these returns should be identical. That is, the standard accounting framework cannot explain why Swedish and Mexican non-migrants have similar returns to schooling, but Swedish immigrants have returns to schooling an order of magnitude greater than Mexican immigrants. Intuitively, a model needs to generate an adjustment process that raises the price per unit of human capital in countries where human capital is scarce. With this feature, non-migrants in developing countries face low education quality, so that a year of schooling generates little human capital; but it is offset by a high price per unit of human capital. Immigrants to the United States face the common U.S. price per unit of human capital, so that returns to schooling for immigrants isolate the effects of education quality. The model features intermediate goods producers with heterogeneous skill intensities that can generate such an adjustment through a relative price effect.

A calibrated version of this model quantitatively replicates the key data moments. I then back out its implications for the importance of quality-adjusted schooling in accounting for cross-country income differences. Quality-adjusted schooling accounts for a factor of 38-41% of the income difference between the top and bottom quintiles of countries. This effect is larger than the 21-24% in the previous literature (Hall and Jones 1999, Hendricks 2002). Consistent with the current literature, I find that years of schooling alone accounts for 27% of income differences. The remainder of the model's income differences are accounted for through education quality. An extension shows that this conclusion is reasonably robust to allowing for ability heterogeneity and ability bias in measured returns to schooling.

The second levels accounting exercise simplifies by *assuming* that the returns to schooling of immigrants are measures of education quality. In this case, sectoral heterogeneity can be removed from the model. The accounting exercise is then an extension of Bils and Klenow (2000). A second step is added to their procedure, where the importance of education quality for income differences is estimated using the responsiveness of average school attainment to measured education quality. Selection of immigrants can be controlled for using an instrumental variables strategy. This exercise yields an estimate that quality-adjusted schooling accounts for 40-42% of cross-country differences in schooling, similar to the calibration exercise. Hence accounting for education quality can also be done using a simple extension of current methods.

The approach to education quality here contrasts with most of the previous work. Since data on education quality is scarce, most research has been driven by models of the education quality production function, which determine what factors augment time in the production of human capital. Bils and Klenow (2000) use a formulation with an input similar to teacher quality, while the recent work of Manuelli and Seshadri (2005), Erosa, Koreshkova, and Restuccia (2007), Cordoba and Ripoll (2007), and You (2008) adopt the Ben-Porath (1967) human capital production function with expenditures as an input. Tamura (2001) has a model with a mixture of the two inputs. This paper provides new estimates of education quality and its importance that are independent of any education quality production function. Independence is a virtue since the education literature is unclear about what attributes produce education quality, and provides a range of estimates for education quality production functions; see Hanushek (1995) and Hanushek (2002) for an overview. In particular, while expenditure on education is often thought to be an important way to improve quality, there is little empirical guidance on the size of the channel. Hence, outside evidence can provide a useful check for this literature. On the other hand, the primary deficiency of not specifying a production function is that this paper can provide no policy prescriptions since it is agnostic about the sources of what are measured to be large quality differences. Their work provides insight on this subject.

The paper proceeds as follows. Section 2 introduces the model and derives the relationships between education quality, returns to schooling, and school attainment. Section 3 collects the data. Section 4 calibrates the model and measures the implied importance of quality-adjusted schooling. Section 5 shows how to account for education quality in a simpler framework similar to Bils and Klenow (2000). Section 6 shows that the main findings are robust to allowing for worker heterogeneity. Section 7 concludes.

2 A Model with Ex-Ante Identical Workers

The baseline model features a continuum of ex-ante identical workers in every country. Since workers are ex-ante identical, ex-post differences in schooling across workers arise only if workers are indifferent among different schooling options. Workers' indifference curves determine the returns to schooling for non-migrants, while firms' demand for skilled labor determines the education levels within and across countries.

2.1 Population Dynamics

The world consists of J closed economies, with individual economies indexed by subscript j. Each economy has a continuum of measure 1 of ex-ante identical infinitely-lived dynasties. A dynasty is a sequence of altruistically linked workers who each live for T_j periods.[4] As soon as a worker dies he is replaced by a young worker who inherits his assets but not his human capital. The date of death across dynasties is staggered so that exactly T_j^{-1} workers die in each year.

[4] Altruistically linked in the standard sense of Barro (1974). I ignore issues related to stochastic mortality; see Tamura (2006), Kalemli-Ozcan, Ryder, and Weil (2000), or Soares (2005) for a model where this uncertainty may be important.

2.2 Dynasties

Each dynasty has the same power felicity function, taken as log for simplicity; generalizing to other functions does not change the results. Preferences over sequences of consumption $C_j(t)$ are then given by:

$$U = \int_0^\infty e^{-\rho t} \log(C_j(t))dt \tag{1}$$

where ρ is the rate of time discounting.

At time t, the dynasty has two sources of income. If the worker has finished school, he earns labor income as a function of his schooling attainment $W_j(S_j(t), t)$; the dynasty also owns and rents out capital, earning returns $R_j(t)K_j(t)$. The dynasty spends this income on consumption $C_j(t)$ and on accumulating capital $\dot{K}_j(t) + \delta K_j(t)$. Then it has a period budget constraint and a dynastic borrowing constraint given by:

$$C_j(t) + \dot{K}_j(t) = W_j(S_j(t), t) + (R_j(t) - \delta)K_j(t) \tag{2}$$

$$\lim_{t\to\infty} K_j(t) \exp\left(-\int_0^t (R_j(\theta) - \delta)d\theta\right) \geq 0 \tag{3}$$

Along the balanced growth path the consumption of workers grows at a constant rate g determined by the growth of aggregate productivity. Then the Euler equation implies that the net of depreciation interest rate $r = R - \delta = \rho + g$. It follows that the capital-output ratio K/Y is constant over countries, so capital does not contribute to cross-country income differences in the usual levels accounting sense. Thus, this framework isolates the impact of quality-adjusted schooling on cross-country income differences.

2.3 Labor-Schooling Decision

The labor-schooling decision is based on the models of Mincer (1958) and Becker (1964). Workers are endowed with one unit of time each period. They allocate their time between schooling and work. Attending school requires workers to forego earnings today, and to pay the costs of current period tuition. Following Bils and Klenow (2000), tuition is a country-specific constant multiple μ_j of the foregone wage, which is a convenient way to capture that tuition typically rises in the schooling level. The benefit to attending school is higher future wages $W_j(S, t)$.

As is standard, workers separate their lives into two periods: they go to school full-time from the beginning of their life until some endogenously chosen age S; then they work full-time until they die. A worker born at time τ then chooses S_j to maximize lifetime income net of tuition costs:

$$\max_{S_j} \int_{\tau+S_j}^{\tau+T_j} e^{-rt} W_j(S_j, t) dt - \int_{\tau}^{\tau+S_j} e^{-rt} \mu_j W_j(t-\tau, t) dt$$

Along the balanced growth path, wages grow at a constant rate g given by aggregate productivity growth. The worker's income maximization problem simplifies to:

$$\frac{(r-g)(1+\mu_j)}{1-\exp[-(r-g)(T_j-S_j)]} = \frac{\partial \log(W_j(S_j))}{\partial S_j} = M_j \tag{4}$$

The local change in log wages with respect to schooling in country j is the Mincerian returns to schooling M_j. There exists a large labor literature estimating regressions of log-wages on schooling and controls which provides useful information. For ease of exposition, I adopt the additional assumption that the equilibrium $T_j - S_j$ is large, so that the denominator of the first expression in equation (4) is one. This assumption yields results the familiar result from the labor literature,

$$M_j = (r-g)(1+\mu_j) = \rho(1+\mu_j) \tag{5}$$

This assumption is dropped for the calibration of the model.

The model predicts Mincerian returns are unaffected by factors such as education quality or the properties of the aggregate production function. The key insight is that for workers to be indifferent among different attainments (as they must be along a balanced growth path), Mincerian returns have to be equal to the opportunity cost of a year of schooling. The opportunity cost depends on the worker's discount rate, which should vary little across countries, and the tuition cost, which can be country specific. Similar to Mincer (1958), this equation defines the indifference curve of the representative worker: workers here are willing to get any level of education as long as they receive an appropriately higher wage. The supply side of the market determines Mincerian returns; the actual attainment is determined by the demand side, which follows.

2.4 Human Capital Production Function

While workers choose schooling solely to maximize income, firms care about the productive value of schooling. The link between schooling and its productive value is provided by the human capital production function. A worker with S years of schooling has human capital:

$$H = \exp\left[\frac{(SQ_j)^\eta}{\eta}\right] \tag{6}$$

Q_j is the exogenous quality of education in country j. The focus here is on measuring education quality, rather than on modeling the allocation of resources or educational institutions that imply Q_j. Education quality is typically determined through a political process involving teachers, parents, voters, and the government, so it is plausible to treat the variable as exogenous to the individual students making decisions on how long to attend school.

The function here is a modified version of the human capital accumulation function of Bils and Klenow (2000) and Klenow and Rodriguez-Clare (1997), particularly in allowing for diminishing returns to schooling. The primary difference is that education quality enters exponentially, rather than multiplicatively as in their formulations. Entering education quality in this way is critical to matching the robust fact that education quality has an effect on workers' decisions about how long to remain in school. Section 3 documents that high education quality countries are also high schooling attainment countries, but there is also significant microeconomic evidence about the same relationship. (Case and Deaton 1999, Hanushek, Lavy, and Hitomi 2006, Hanushek and Woessmann 2007). The assumption $0 < \eta < 1$ is also necessary to obtain this result, so it is maintained throughout.

2.5 Intermediate Goods Producers

Workers in this model are indifferent among any schooling attainment, as long as they get paid a return of $\rho(1 + \mu_j)$ per year. The distribution of schooling choices within a country is driven by heterogeneity in the demand for skilled labor. Heterogeneity comes from a set of sectors producing differentiated intermediate goods with heterogeneous skill intensity indexed by the parameter γ. Sectors (and their skill intensities) are distributed uniformly on $[\underline{\gamma}, \bar{\gamma}]$. Sectors are loosely interpreted as occupations or industries. Sections 3 and 4 connect the model properties to data on both industries and occupations.

Output in sector γ is given by the production function:

$$Y_j(\gamma) = K_j(\gamma)^\alpha \left(A_j H_j(\gamma)^\gamma L_j(\gamma)\right)^{1-\alpha}$$

where A_j is the labor-augmenting efficiency level general to the entire country, $K_j(\gamma)$ and $L_j(\gamma)$ are the capital and labor choices specific to the sector, and $H_j(\gamma)$ is the human capital per worker in the sector. Efficiency grows exogenously at rate g. Given the human capital accumulation function in equation (6), higher γ sectors are more skill-intensive.

The standard levels accounting analysis with human capital assumes a single aggregate technology with $\gamma = 1$ (Bils and Klenow 2000, Hall and Jones 1999). Section 5 documents that the aggregate technology model is inconsistent with the zero or weakly negative correlation between the returns to schooling of immigrants and non-migrants. Allowing for continuous technological heterogeneity creates a relative price effect that can explain these facts. It also generates closed-form solutions for the key wage equations and is easily compared with the aggregate technology model common in the literature.

There is a large set of potential entrants, so that no profits are earned and the equilibrium number of firms in each sector is indeterminate. Then a sector γ firm takes the real price of its output $P_j(\gamma)$, the rental price of capital R, and the schedule of wages $W_j(S)$ as given. It chooses the capital stock, labor hours, and level of schooling per worker to maximize profits each period. Substituting in for human capital, the firm's problem is:

$$\max_{K_j(\gamma),L_j(\gamma),S_j(\gamma)} P_j(\gamma)K_j(\gamma)^{\alpha}\left\{A_j \exp\left[\frac{\gamma}{\eta}(S_j(\gamma)Q_j)^{\eta}\right]L_j(\gamma)\right\}^{1-\alpha} - RK_j(\gamma) - W_j(S_j(\gamma))L_j(\gamma) \tag{7}$$

Combining the firm's first-order conditions for labor and schooling yields its equilibrium demand for schooling:

$$\frac{\partial \log(W(S_j(\gamma)))}{\partial S_j(\gamma)} = M_j = \gamma S_j(\gamma)^{\eta-1}Q_j^{\eta} \tag{8}$$

$$S_j(\gamma) = \left[\frac{\gamma Q_j^{\eta}}{\rho(1+\mu_j)}\right]^{1/(1-\eta)} \tag{9}$$

Since all domestic workers share the same education quality, a unique education level satisfies equation (9). Given $0 < \eta < 1$, higher education quality leads to higher average schooling attainment across countries, and higher skill intensity leads to higher schooling attainment within a country. This equation also motivates the restriction that the support of γ be bounded and positive; $\gamma < 0$ implies schooling is unproductive in that sector, while large γ imply students should spend most of their life in school. The bounded and uniform distribution above is the simplest to satisfy these intuitive requirements; experiments with other distributions with these features yielded similar quantitative results.[5]

[5] For instance, the parameters but not the main results of the calibration would change with a triangular distribution. Further, Section 5 shows that similar results obtain in an exercise without sectoral

2.6 Final Goods Producer

A zero-profit final-goods producer purchases $X_j(\gamma)$ of each of the intermediate goods and aggregates them into the final good, which she sells to the consumers. The producer uses a CES technology with elasticity ψ. The final good is the numeraire for the economy. Then the final goods producer's problem is to maximize:

$$\max_{X_j(\gamma)} \left[\int_{\underline{\gamma}}^{\bar{\gamma}} (X_j(\gamma))^{1-1/\psi} d\gamma \right]^{\psi/(\psi-1)} - \int_{\underline{\gamma}}^{\bar{\gamma}} P_j(\gamma) X_j(\gamma) d\gamma \tag{10}$$

Final output is used for consumption and investment. Market clearing conditions, the definition of equilibrium, and the definition of a balanced growth path are all given in Appendix A.

Given the CES technology, all varieties will be produced in all countries in equilibrium. The price, quantity, and employment in each sector is determined to be consistent with the final goods producer's demand equation. Along a balanced growth path, the supply of labor for different schooling levels is consistent with the labor demand of firms.

2.7 Immigrants

Consider the wages of workers employed in two different sectors. These workers will have different school attainment and different human capital. Their relative wages are affected by their relative human capital levels, but also by the relative prices of sectoral outputs:

$$\frac{W_j(\gamma)}{W_j(\gamma')} = \frac{H_j(\gamma)}{H_j(\gamma')} \left(\frac{P_j(\gamma)}{P_j(\gamma')} \right)^{1/(1-\alpha)}$$

Relative prices vary systematically with the human capital stock in the model: human capital abundant countries have lower relative prices of skill-intensive goods. This relative price effect is missing from a simpler accounting exercise. It is the feature that allows the model to explain the negative correlation between returns to schooling for immigrants and non-migrants. Looking at wage data for non-migrants confounds human capital differences and relative prices. Immigrants to the United States provide a natural way to circumvent this problem, since immigrants will have acquired education with a different quality in their foreign country, but they will all face the same aggregate labor market conditions in the United States. On the other hand, since immigrants are a selected sample of the people

heterogeneity.

who were educated in their birth country, immigrant selection complicates this inference.

Given the structure of the model, wages are linear in schooling for American non-migrants, regardless of education quality. To motivate discussion of selection in a manner consistent with the immigration literature, suppose that Americans also vary in their endowment of a second attribute, such as willingness to exert effort or non-cognitive ability. Assume that this enters the log-wage expression linearly, so that augmented wages are given by:

$$\log(W) = c + \rho(1 + \mu_{US})S + \varepsilon \tag{11}$$

where c is a constant. If non-cognitive ability ε is normally distributed with mean normalized to 0, then log-wages will also be normal, approximately consistent with the data.

Workers in country j complete their education abroad, with prevailing foreign education quality Q_j. Some of these workers subsequently immigrate to the United States. Those who enter may be selected on observable characteristics (S) but may also be selected on their non-cognitive characteristics, either because U.S. policy selects on these characteristics, or through a process of self-selection as in Borjas (1987). Immigrants earn the same wages as Americans with the same human capital. Using equations (6) and (11) yields the immigrant wage expression:

$$\log(W) = c + \rho(1 + \mu_{US})\frac{Q_j}{Q_{US}}S + \varepsilon_{US}^j \tag{12}$$

where ε_{US}^j denotes the non-cognitive ability of workers who immigrate from country j.[6] Inferences based on average wages of immigrants from country j will be biased if immigrants are selected so that $E(\varepsilon_{US}^j) \neq 0$. However, the slope of the wage regression with respect to schooling yields the important information:

$$M_{US}^j = \frac{Q_j}{Q_{US}} M_{US} \tag{13}$$

The returns to foreign schooling M_{US}^j are directly proportional to the relative education quality of the foreign schooling. Hence, the baseline empirical analysis uses a regression of the form of equation (12), with separate country of origin fixed effects (to control for $E(\varepsilon_{US}^j)$) and separate country of origin returns to schooling (to measure $\frac{Q_j}{Q_{US}}$).

[6] This wage expression follows if sector skill intensity only interacts with education human capital $H(S, Q)$ and not non-cognitive abilities ε.

3 Cross-Country Data on Schooling

3.1 Four Sources of Data

The model makes predictions about the relationships between education quality, school attainment, and the returns to schooling for migrants and non-migrants. This section documents and constructs the four sources of data. It also tests the model's predictions.

Data on schooling attainment is average years of schooling in the over-25 population of different countries in 1999, taken from the Barro-Lee data set (Barro and Lee 2001). Scores on internationally standardized achievement tests are taken from Hanushek and Kimko (2000), series QL2*. They construct a test score index for a broad cross-section of countries by aggregating a series of different testing programs running from 1966-1991. Aggregated test scores from the OECD PISA exam in 2000/2003 and the U.S. Department of Education TIMSS exam in 1995/1999/2003 are also used as checks at a few points. Returns to schooling for non-migrants are commonly measured using Mincerian returns gathered from a regression of log-wages on schooling and a series of controls. I use a set of estimates covering many countries gathered by Banerjee and Duflo (2005); their work is an update of Psacharopoulos and Patrinos (2004).

Finally, I estimate the returns to schooling of immigrants to the United States. Estimation follows Card and Krueger (1992), who use the returns to schooling of cross-state migrants to identify the education quality of the migrants' source state. Their idea was previously extended to cross-country immigrants by Bratsberg and Terrell (2002); I repeat their exercise with a few changes using 2000 U.S. Census data. U.S. Census data is ideal because it covers a large sample of immigrants from many different countries and contains information on wages, schooling attainment, and language ability, as well as variables that make it possible to impute which immigrants likely completed their schooling abroad. The regression equation is:

$$\log(W_{US}^{j,k}) = b^j + M_{US}^j S_{US}^{j,k} + \beta X_{US}^{j,k} + \varepsilon_{US}^{j,k} \tag{14}$$

where $W_{US}^{j,k}$ is the wage of immigrant k from country j in the United States. b^j is a country-of-origin fixed effect, M_{US}^j is the returns to country j schooling in the United States, and $X_{US}^{j,k}$ is a vector of control variables. The country of origin fixed effect is intended to control for differences in selection on non-cognitive ability, as discussed previously. The estimates then capture the wage gain to an additional year of Mexican education for Mexican immigrants to the United States, compared to the wage gain of an additional year of Swedish education for Swedish immigrants to the United States.

I implement this equation using the 5% sample of the 2000 Census Public Use Micro Survey, made available through the IPUMS system (Ruggles, Sobek, Alexander, Fitch, Goeken, Hall, King, and Ronnander 2004). Immigrants are identified by country of birth.[7] The Census lists separately each of 130 statistical entities with at least 10,000 immigrants counted in the United States. Some of these statistical entities are nonstandard: for instance, there are response categories for Czechoslovakia, the Czech Republic, and Slovakia, since immigrants came both before and after the split. I refer to these statistical entities as countries as a shorthand. I keep as many countries as are separately identified, except that the United Kingdom is merged into a single observation.

The Census includes a measure of schooling attainment which I recode as years of schooling in the usual manner. The Census does not provide direct information on where the schooling was obtained. Instead, I use information on age, year of immigration, and schooling attainment to impute which immigrants likely completed their schooling abroad. It is important to exclude from the sample immigrants who may have received some or all of their education within the United States to have an unbiased estimate of source-country education quality. The baseline sample uses a six year buffer between expected date of completing schooling and year of immigration to minimize measurement error for immigrants who repeat grades, start school late, or experience interruptions in their education. Thus, high school graduates have to be at least age 24 when they immigrate to be included (expected to complete at age 18, plus 6 years as a buffer).

The sample includes respondents aged 19-64 who were employed but not self-employed in the previous year, and who reported working at least 30 weeks in the previous year and at least 30 hours per week. The wage is calculated as previous year's average hourly wage, computed using annual wage income, weeks worked, and usual hours per week. The vector of controls includes age and its square, gender, a dummy for residence in metropolitan area, a set of dummies for self-assessed English language proficiency on a five-option scale, dummies for Census region of residence, a disability dummy, and a full set of year of immigration dummies. The final sample includes 4.3 million Americans and 240,000 immigrants from 130 different source countries.

[7] A potential bias could arise if immigrants are born in one country but receive their schooling in another. However, 89% of immigrants who were living abroad five years prior to the Census were living in their birth country.

Table 1: Pairwise Correlation of Key Variables

	Returns, Immigrants[a]	Test Scores[b]	Years Schooling	Real GDP p.w.	Returns, Non-Migrants[c]
Ret., Imm.	1.00				
Test Scores	0.46	1.00			
Years	0.61	0.73	1.00		
Real GDP p.w.	0.57	0.52	0.78	1.00	
Ret., Non-Mig.	-0.08	-0.28	-0.29	-0.23	1.00

[a] Returns to schooling of immigrants in the United States, from Table 11.

[b] Hanushek-Kimko aggregated scores on internationally standardized achievement tests (Hanushek and Kimko 2000).

[c] Returns to schooling among non-migrants in the home country (Banerjee and Duflo 2005).

3.2 Measures of Education Quality

Appendix B provides regression results, including number of observations per country and standard errors. The measured U.S. returns are 9.2%. Results from other countries vary widely. The highest returns are observed for immigrants from Norway, Japan, Sweden, and Tanzania, all over 10%. A few countries have negative returns, although none of these coefficients is statistically significant. Two useful benchmarks on the low end of the scale are Laos and Mexico, with 0.4% and 0.9% returns estimated with a large sample of immigrants.

Table 1 summarizes the data by looking at the pairwise correlations between the four pieces of data. The correlations bear out the main predictions of the model. Test scores, average attainment, and returns to schooling for immigrants are highly correlated. They are also correlated with development status, suggesting education quality may play a role in cross-country income differences. Finally, all other terms are weakly negatively correlated with Mincerian returns, while the baseline model predicts no correlation.

The diverging returns for immigrants and non-migrants is consistent with a novel prediction of this model. A particular illustration may help. Data from test scores indicate that Swedish students have access to much higher education quality than do Mexican students. On the 2003 PISA exam mathematics section, a Swedish student one standard deviation below mean would have outscored the average Mexican student. The returns to schooling of Swedish and Mexican immigrants convey this information: 0.9% per year for Mexican immigrants, against 11.4% per year for Swedish immigrants. However, the returns for non-migrants do not: the Mincerian returns to schooling are actually higher in Mexico.

3.3 Comparison with Hendricks (2002)

Hendricks (2002) uses information on the wages of immigrants to the U.S. to measure cross-country differences in human capital. He finds that immigrants earn similar wages to natives, and argues for the implication that human capital cannot account for the bulk of cross-country income differences. This paper uses different evidence. Hendricks uses a non-parametric estimate of immigrant wages that is close in spirit to regressing:

$$\log(W_{US}^{j,k}) = b^j + MS_{US}^{j,k} + \beta X_{US}^{j,k} + \varepsilon_{US}^{j,k}$$

although he does not impose linearity restrictions. His methodology values observable characteristics such as schooling and experience the same across birth countries; he then uses b^j, the unexplained level difference in wages, as the variable of interest.

Measurement based on b^j has to be interpreted as the total unobserved human capital difference. It includes factors such as health, on-the-job training, and non-cognitive ability. Since the fixed effect captures the total unobserved human capital difference, it also captures differences that are due to the selection of immigrants. Hence, if immigrants are positively selected, Hendricks' measurement underestimates the role of human capital. Hendricks argues that no plausible amount of selection allows human capital to account for all of cross-country income differences. However, recent work has noted that this bounding argument still leaves a lot of room for human capital, and some papers have argued that human capital can account for all of income differences and still be consistent with Hendricks' estimates (Manuelli and Seshadri 2005).

Motivated by the model in Section 2, this paper estimates differences in the U.S. returns to foreign schooling, which is a narrow measure of education quality.[8] Focusing on returns allows for a different approach to immigrant selection. By discarding the country-of-origin fixed effect I am able to control for some selection. Section 3.5 shows that only a narrow form of selection would overturn this paper's results. Finally, test scores offer a natural instrument for potentially biased measures of education quality, an approach pursued in Section 5.

Hanushek and Kimko (2000) also use immigrants to understand the role of human capital in explaining cross-country income differences. In particular, they show that immigrants from countries with higher test scores (QL2*, the same test score measure used here) earn higher wage levels. Based on the model of Section 3 and the data, this paper argues

[8] Cunha and Heckman (2007) have suggested that school outcomes and other components of human capital may not be separable, which is implicit in this paper's decomposition but not Hendricks' work.

that education quality is better associated with higher returns to schooling. An additional advantage of the current framework is that it makes precise the methodology for aggregating micro-level effects.

3.4 Robustness

The estimated returns to schooling are robust to sample restrictions. They are highly correlated with estimates from a sample including only men or from a sample excluding Americans (who currently affect coefficients on common parameters such as Census region dummies). They are robust to alternative ways of excluding immigrants who may have received some American schooling, such as allowing for a three, nine, or twelve year buffer. I also experiment with including immigrants who likely have mixed-country schooling. In this case I assign each year of schooling to the country in which it was likely received and re-estimate returns; similar but noisier results obtain. The returns also appear to be consistent over time: estimating separate returns for pre and post-1985 cohorts, or estimating returns using 1990 and 1980 Censuses, gives similar results. The correlation of each of these sets of estimates with the baseline estimates is greater than one half.

To understand what drives the estimates, I cut the sample by English language ability and education level. For English language ability I estimate separate regressions for immigrants that speak only English or speak English very well versus those that speak it well, not well, or not at all. The baseline estimates are highly correlated with returns for English speakers and modestly correlated with returns for non-English speakers, 0.85 against 0.45. I then perform a similar exercise cutting immigrants into those with at least a high school degree and those with less. In this case, baseline estimates are highly correlated with those of highly-educated immigrants, not those of less-educated immigrants, 0.65 against 0.23. The results are driven by large differences in rates of return among well-educated, English proficient immigrants from around the world. They are consistent with the findings of Jones (2008) that wage gaps are concentrated among college graduates who enter the U.S. after age 30.

The estimates are strongly correlated with independent measures of education quality. The three sets of tests used here are the Hanushek-Kimko measures (their QL2*, correlation of 0.46), the PISA measures (0.61) and the TIMSS measures (0.25). Other factors, including the similarity of the foreign country (as measured by British legal origins, English as a main or official language, or PPP income per capita, for instance) help predict measured returns, although test scores are still statistically significantly related after controlling for these factors.

3.5 Differential Selection

The previous section indicated that estimated rates of return to foreign schooling are robust to many of the details of measurement. Generally, there is a consistent, positive relationship between estimated returns to foreign schooling and education quality, development status, and school attainment. However, it may be the case that this relationship is not driven by education quality, but by a particular form of differential selection among immigrants.[9]

For example, take an alternative hypothesis that explains the empirical correlation between estimated returns and development status. In this hypothesis, the returns to foreign schooling would be the same for all countries if a random sample of workers were chosen to immigrate. Suppose that immigrants from developed countries and highly-educated immigrants from developing country are all selected by an equal margin. However, perhaps less-educated immigrants from developing countries are more strongly selected: to earn access through official immigration channels, they are exceptional in some attributes that are unobservable to the econometrician. Because they are exceptional in their unobservable attributes, they will also earn high wages for their education, which artificially flattens the wage-schooling profile and generates low measured returns for developing countries. More generally any selection which generates

$$\left[E(\varepsilon_{US}^{j}|S^{Low},Y^{Low}) - E(\varepsilon_{US}^{j}|S^{High},Y^{Low})\right] > \left[E(\varepsilon_{US}^{j}|S^{Low},Y^{High}) - E(\varepsilon_{US}^{j}|S^{High},Y^{High})\right],$$

could also explain the observed pattern.

Three pieces of evidence suggest that this hypothesis is unlikely to explain a significant fraction of the empirical returns-development status relationship. First, recall from the previous section that estimates of the rate of return are driven mostly by differences in estimated returns for those with at least a high school education. Differential selection for these workers seems less likely, particularly given that relatively few immigrants enter the U.S. on employment visas (around 13%; see below).

Second, the implied degree of selection needed to explain the entire relationship is large. For example, suppose that the true value of a year of schooling is 9.2%, the measured value for natives. The estimated return for immigrants from many developing countries is in the range of 0-2%, indicating that workers with, say, high school and college degrees have nearly the same human capital. Selection could explain this finding, but it requires that high school graduates from developing countries be much more selected than college graduates from developing countries. In particular, it requires that the extra unobserved

[9] I am indebted to an anonymous referee for suggesting this term and the following hypothesis.

characteristics of high school graduates have nearly the same value as a college education to explain why these two groups earn similar wages. Measured at U.S. values, the extra unobserved characteristics would be valued at 36.8% of wages.

Finally, I exploit some information from variation in the degree of selection created by formal U.S. immigration policy. The U.S. government divides legal immigrants into different possible visa classes upon entry. I aggregate these into four groups: a family reunification group (family-sponsored preferences plus relatives of citizens); employment preferences; refugees and asylees; and an other category (diversity preferences to promote immigration from historically under-represented countries, plus several miscellaneous groups). These groups differ substantially in terms of how selected they are for labor market potential. For instance, Jasso, Massey, Rosenzweig, and Smith (2000) found that immigrants with employment visas had 3.3 years more education as compared to refugees/asylees. They were also more likely to be employed shortly after admission, and had median earnings about 2.5 times higher than refugees/asylees.

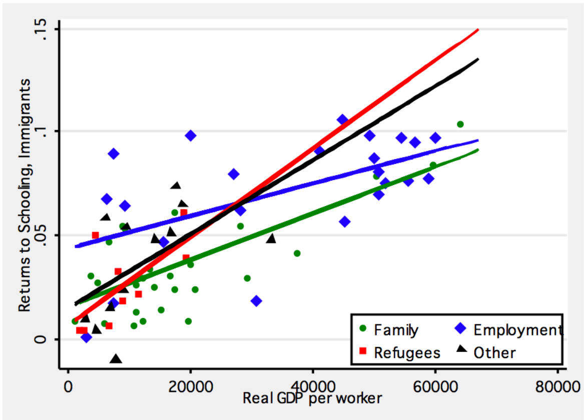
The composition of each country's immigrants by visa class also varies substantially. To quantify this, I aggregate information on immigration flows by visa class and country of origin from 1998-2000 (U.S. Immigration and Naturalization Service 1998-2000). I then identify countries with "high" concentrations of a particular visa class. A high concentration of family reunification visas is defined as more than 80% of visas granted to that country; for employment, high is more than 25%; for refugees and asylees, 50%, and for other, 50%.[10]

I then ask whether the relationship between estimated returns and development status or the average schooling of non-migrants is consistent across these sets of countries with very different compositions by visa class. Too few countries participated in international testing to use that relationship. The results are in Figure 1. Each point is a specific country in one of the above groups, color-coded by group. Best-fit lines are included.[11] Although the exact relationship varies, the results always indicate a strong positive relationship between estimated returns and development status or average attainment. This relationship holds for countries whose emigrants are predominantly refugees escaping persecution and for countries whose emigrants are predominantly relatives of current residents of the U.S.

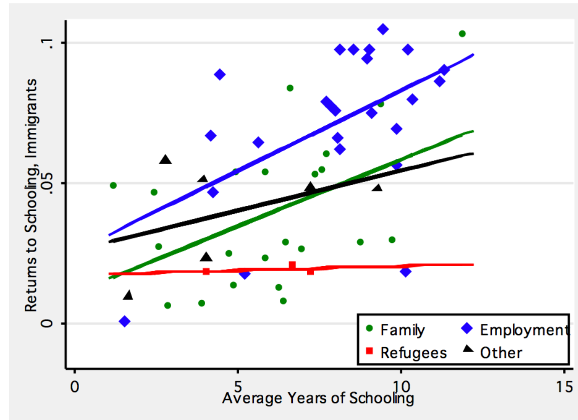
Ultimately, it is difficult to categorically rule out selection based on unobserved charac-

[10]The different thresholds are necessary because immigration flows are not balanced by class. In the year 2000, the overall rates were 69% for family reunification; 13% for employment-sponsored; 8% for refugees/asylees; and 10% for other. Further, employment-sponsored visas are much more dispersed across countries than the last two classes.

[11]For Figure 1a the trend lines are significant at the 99%, 99%, 90%, and 90% levels (family, employment, refugees, other). For Figure 1b, the trend lines for family and employment are significant at the 99% levels, while the other trend lines are insignificant with three and six observations.



(a) Development Status



(b) School Attainment

Figure 1: Returns to Schooling and Class of Immigration

teristics. The point of this section is to clarify that only differential selection could explain the empirical patterns of this paper. Differential selection would need to apply to immigrants with at least a high school education, it would need to be large, and it would need to be uncorrelated with large differences in the types of immigrants the U.S. accepts from different countries.

3.6 Other Education Quality Predictions

The model predicts that conditional on schooling attainment, immigrants from low education-quality countries have less human capital and work in less skill-intensive sectors. Sectors here can be loosely thought of as occupations or industries. Following Jones (2008), I order Census-level occupations and industries by their skill intensity as measured by the modal educational attainment of Americans who work in that occupation or industry. Using average attainment yields similar results. I condition on high school or college attainment for immigrants, the most common levels in the data. Table 2 gives the results.

Immigrants from high education-quality countries work in more skill-intensive occupations and industries (work with more educated Americans). The link is stronger for occupations and stronger for college graduates, but it is statistically significant for all four groups. Hanushek-Kimko test scores have a standard deviation of 13.2, so at the upper end (college-occupations) a one standard deviation increase in test scores implies working with Americans with one-third year more schooling; the difference between the lowest and

Table 2: Industry and Occupation Skill Intensity for Immigrants

	High School		College	
	Industry	Occupation	Industry	Occupation
Test Scores	0.0052	0.0093	0.0070	0.0268
	(0.0019)	(0.0024)	(0.0022)	(0.0040)
R^2	0.10	0.17	0.12	0.38

Standard errors are in parentheses. Dependent variable is skill intensity of the immigrant's industry or occupation, measured as modal attainment of Americans in the same industry or occupation. Regression is conditional on either high school or college attainment.

highest test scores translates to working with Americans with almost 1.5 more years of schooling.

4 Calibration of the Model

4.1 Fixing Model Parameters

The model generates qualitative predictions consistent with the data in Table 1. This section uses a calibration exercise to show that the model can quantitatively replicate the key facts about education quality, attainment, and returns to schooling introduced in the last section. It then measures the importance of quality-adjusted in accounting for cross-country income differences. Throughout, A_j is normalized to one for all countries, so that estimates reflect the importance of human capital alone in accounting for income differences. Then calibration requires J countries with variables (Q_j, T_j) to use as exogenous inputs to the model and variables (M_j, S_j, Y_j) to compare to the predictions of the model.

Values of Q_j are taken from returns to immigrant schooling; see Table 11. T_j, the potential working life span in country j, is taken to start at age 5 and continue until the average worker dies or retires. Hence, T_j equals the country's age 5 life expectancy (worker expects to die before retirement at 65) or 60 (retirement at 65), whichever is smaller.[12] Schooling and average Mincerian returns use the data discussed in Section 3. Finally, I compare the model's income predictions to the data values for Y_j, measured as PPP

[12]Age 5 life expectancy is estimated using data on life expectancy at birth, infant mortality rate, and under 5 mortality rate, taken from the 2005 Human Development Report (Denny 2005). I assume that infants who die before age 1 live 0.25 years on average, and that those who die between ages 1 and 5 live 3 years on average.

Table 3: Representative Quintiles

	Quintile					
Observation	1	2	3	4	5	U.S.
M_{US}^j	3.0%	4.0%	3.8%	5.1%	7.7%	9.2%
M_j	8.4%	11.5%	9.9%	9.3%	8.1%	9.2%
Age 5 LE	58.1	59.2	60	59.7	60	60
PPP GDP p.w.	3,120	8,360	14,100	26,400	53,600	67,100
Schooling	2.67	5.08	5.82	7.68	9.25	12.2

M_{US}^j and M_j are the log-wage returns to schooling of emigrants to the U.S. and non-migrants. Age 5 life expectancy is calculated and capped as explained in the text. PPP GDP per worker is taken from Penn World Tables 6.2 for year 2000 (Heston, Summers, and Aten 2006). Schooling is average years of schooling from Barro-Lee.

income per worker (Heston, Summers, and Aten 2006).

Relatively few, mostly developed countries have all five of these variables available. To avoid discarding a large fraction of the sample, the countries are aggregated. I take the 118 countries that have data for both Y_j and Q_j and form them into five quintiles by Y_j. For each quintile, the values $(Q_j, T_j, S_j, M_j, Y_j)$ are the average values for the quintile, ignoring missing observations. Table 3 gives the resulting values for the five quintiles. Results are also calibrated for the United States separately, to facilitate construction of certain moments as explained below; U.S. data are also given in Table 3.

The model requires the parameters g, α, δ, ρ, $\underline{\gamma}$, $\bar{\gamma}$, ψ, η, and μ_j be specified. Additionally, since returns to schooling for immigrants identifies education quality relative to the U.S. level, it is necessary to calibrate one normalization $\bar{Q}$; then each country's education quality is $Q_j = M_{US}^j \bar{Q}$. Some of these parameters are standard from the literature, so $\alpha = 1/3$, $\delta = 0.06$, and $\rho = 0.05$ are set outside the model. $g = 1.75\%$ is also taken from outside evidence (Barro and Sala-i-Martin (1999), p.3). The accounting literature is built around a standard neoclassical aggregate production function equivalent to having a single technology with $\gamma = 1$, so the distribution $[\underline{\gamma}, \bar{\gamma}]$ is centered on $\gamma = 1$ to make the results more comparable with the existing literature. Finally, μ_j is restricted to be the same for all countries.

Then there are 5 parameters calibrated in the model: η, ψ, $\bar{\gamma}$, $\bar{Q}$, and μ. μ governs the Mincerian returns to schooling, so it is set to match the world-average returns of 9.44% for this parameter. $\bar{Q}$ and η govern the level of schooling and the elasticity of schooling with respect to quality, from equation (9). They are chosen to fit the schooling level of the highest quintile of 9.25 years (using the average across quintiles works similarly), and the elasticity of schooling with respect to quality across the five quintiles, 1.21.

$\bar{\gamma}$ governs the heterogeneity of sectors and school attainment within a country. It is calibrated to the coefficient of variation for schooling in the sample of Americans used in Section 3 of 0.234. To calibrate ψ I turn to evidence from Hendricks (2009). He decomposes cross-country schooling differences into those that occur within industries and those that occur through the reallocation of labor across industries. He finds that about three-fourths of the total change can be decomposed within industries. This model suggests education quality could be the force that raises attainment for all industries. In the model, within-sector differences can be found by comparing equation (9) across countries with assumed identical μ_j to yield:

$$\frac{S_j(\gamma)}{S_i(\gamma)} = \left(\frac{Q_j}{Q_i}\right)^{\eta/(1-\eta)}$$

So within-sector differences are affected by education quality and η, while differences in employment across sectors are affected by ψ. I use this moment to calibrate the value of ψ.

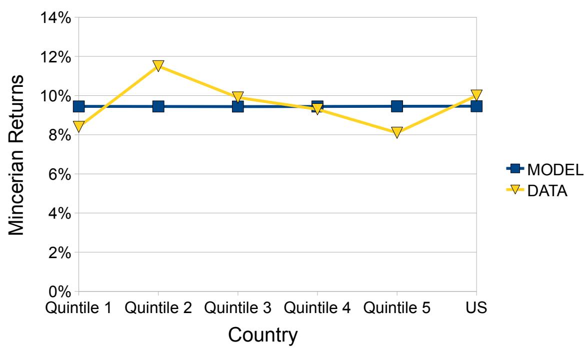
Table 4: Baseline Model Calibrated Parameters

Parameter	Role	Value
	Calibrated to Outside Evidence	
α	Capital Share	0.33
δ	Capital Depreciation Rate	0.06
ρ	Time Discount Rate	0.05
g	Rate of Efficiency Growth	1.75%
	Calibrated to Fit Data	
μ	Average Mincerian Return, Quintiles 1-5	0.88
$\bar{Q}$	Schooling in Quintile 5	0.55
η	Elasticity of Schooling w.r.t. Quality, Quintiles 1-5	0.49
$\underline{\gamma}$	Coefficient of Variation in Schooling, U.S.	0.42
$\bar{\gamma}$	Coefficient of Variation in Schooling, U.S.	1.58
ψ	Within-Industry Educational Differences, U.S. - Quintile 1	8.2

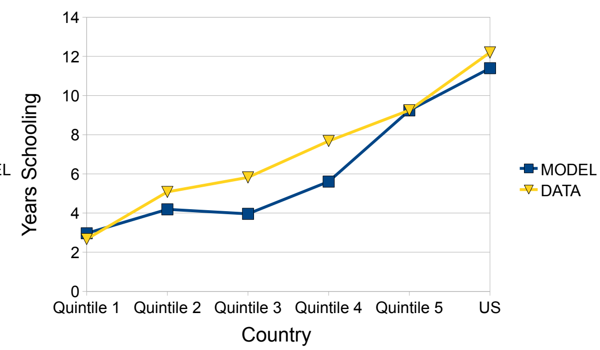
Since the model has as many parameters as moments, it fits each moment exactly. Table 4 lists the full set of parameters and the calibrated values. $\mu = 0.88$ implies that the direct costs of a year of schooling are 88% of the foregone wages. This number is in line with U.S. data suggesting that the total cost of attending a 4-year public college is 65% of the median annual earnings of a new college graduate, while total cost of attending a 4-year private college is 135%.[13] $\eta = 0.49$ is slightly larger than the $\eta = 0.4$ estimated in Bils and Klenow (2000), in a different context. The range of skill intensity across sectors is fairly broad, and intermediates of different sectors are good substitutes, consistent with the general estimated elasticity across detailed products in the trade literature.

4.2 Model Fit and Income Differences

The model fits the five targets above, but they include only average Mincerian returns and the schooling of the fifth income quintile. The entire profiles of schooling and Mincerian returns for the model and data are given in Figure 2. The model fits the schooling of the first and fifth quintiles closely; these are the quintiles used for income comparisons. By allowing the μ_j to vary, the calibration can fit the entire Mincerian returns profile, but this worsens the fit for the schooling profile. Likewise it can match the schooling profile, which worsens the fit for Mincerian returns. These baseline figures are a reasonable compromise.[14]



(a) Predicted vs. Actual M_j



(b) Predicted vs. Actual S_j

Figure 2: Calibrated Model vs. Data

Given that the model provides a good quantitative fit to the data, I now measure its predictions for the role of quality-adjusted education in accounting for cross-country income differences. Table 5 gives the model-generated difference in PPP GDP per worker between the first and fifth income quintiles. In the data, output per worker varies by a factor of

[13]Data on costs are taken from Baum and Ma (2007b), Figure 2; median earnings are taken from Baum and Ma (2007a), Figure 1.3

[14]The model is less sensitive to the values for ψ and $\bar{\gamma}$. For example, if ψ is set to 2 instead of calibrated, the model accounts for 39% of income differences, instead of 40% in the baseline. If $\psi = 16$ the model accounts for 37%; if $\bar{\gamma} = 1.25$, the model accounts for 39%.

Table 5: Income Differences Due to Schooling

	Income Ratio	% Accounted For
Data	17.2	100%
Baseline Model, One Good Interpretation	3.11	40%
Baseline Model, PPP Interpretation	2.94 - 3.24	38 - 41%
Experiment 1: Only S Varies	2.14	27%
Experiment 2: Only Q Varies	1.94	23%
Literature: Hall and Jones (1999)	1.91	24%
Literature: Hendricks (2002)	1.69	21%
Literature: Erosa, Koreshkova, and Restuccia (2007)	4	46%

17.2 across these quintiles. The model predicts output per worker variation of a factor of 3.11, accounting for $\frac{\log(3.11)}{\log(17.2)} = 40\%$ of the total income difference.

For the baseline measurement the CES function is treated as a final goods producer. An alternative interpretation is that consumers purchase and consume intermediate goods directly, with a CES utility aggregator across goods. Either interpretation is equally plausible, but the second necessitates a PPP-style price correction to compare outputs across countries. I perform five such corrections, using each of the five quintile's prices. The model predicts similar variation in output, ranging from a factor of 2.94 using quintile 5's prices to a factor of 3.24 using quintile 1's prices.[15] Hence I conclude that the predictions are insensitive to the normalization of a final goods producer.

Table 5 also includes the results of two experiments that disentangle the role of education quality versus years of schooling. In the first experiment, all countries are counterfactually assigned the education quality of Quintile 5, so that only years of schooling varies. Then human capital accounts for 27% of income differences. For Experiment 2, all countries are counterfactually assigned the average attainment of Quintile 5, so that only education quality varies. Then human capital accounts for 23% of income differences. Accounting for education quality is nearly as important as accounting for years of schooling.

The role for years of schooling alone closely agrees with the previous literature. For example, Hall and Jones (1999) do a similar exercise that accounts only for years of school-

[15] Given the high elasticity of substitution, relative prices are reasonably similar across countries. Then the closed economy framework may be a reasonable starting assumption. Extending the model to allow for trade, but including realistic trade barriers, is unlikely to have much impact in the face of these small price differences. The empirical evidence suggests that factor price equalization does not hold (Schott 2003). In this case factor endowments affect factor prices, the main mechanism of the model.

ing. They find that years of schooling account for 24% of income differences between the top and bottom quintiles, against 27% here. Hence, the larger total role for schooling - an extra 13% of income differences accounted for - comes solely through education quality accounting. Similarly, these numbers are larger than the benchmark numbers in Hendricks (2002). On the other hand, they are slightly smaller than the most comparable numbers from the endogenous school quality literature, accounting for 40% as opposed to 49% in Erosa, Koreshkova, and Restuccia (2007).[16]

5 An Aggregate Production Function Approach

The standard growth accounting models feature a Cobb-Douglas aggregate production function in place of the sectoral heterogeneity used here. Sectoral heterogeneity complicates the model, so it is worth asking how far the simpler model can go. Replace the continuum of sectors and the final goods producer with the standard Cobb-Douglas production function

$$Y_j = (K_j)^{\alpha}(A_j H_j L_j)^{1-\alpha} \tag{15}$$

while human capital is still determined by equation (6). Assume that workers face the same problem as outlined in Sections 2.1-2.3. Finally, maintain the assumption that markets are competitive. Then the setup is essentially the same as Bils and Klenow (2000) with education quality differences and endogenous school choice.

In this case, the model's predictions about the key variables can be summarized by:

$$S_j = \left[\frac{Q_j^{\eta}}{\rho(1+\mu_j)}\right]^{1/(1-\eta)} \tag{16}$$

$$M_j = M_{US}^j = \rho(1+\mu_j) \tag{17}$$

Without heterogeneity on the demand side, all workers in a country choose the same schooling. This point can easily be addressed by including worker heterogeneity, such as discount rate or ability heterogeneity. The more troubling prediction comes from equation (17): migrants and non-migrants from country j should earn the same return to schooling.

The standard levels accounting setup is inconsistent with the basic fact of this paper

[16] The same mapping from countries to quintiles is used for all papers. The fraction of income accounted for takes into consideration that different countries were available for each paper. For example, the Erosa, Koreshkova, and Restuccia (2007) figure is for two hypothetical countries that differ by a factor of 20 in income, so the fraction accounted for is $\frac{\log(4)}{\log(20)} = 46\%$. Section 5 contains country-by-country comparisons as well.

that the returns to schooling for immigrants, but not non-migrants, consistently vary with education quality. Since it predicts that returns will be the same, it cannot motivate why returns to schooling for immigrants but not non-migrants are a useful measure of education quality. The baseline model shows how the accounting framework can be extended to be consistent with all this data, and motivates using returns to schooling for immigrants.[17] Sectoral heterogeneity also provides additional checks on the model, in terms of the industries and occupations of immigrants and the relative contribution of within-industry skill upgrading. The apparent tradeoff is that constructing countries' human capital stocks is more complicated than in Bils and Klenow (2000). The next section shows how to simplify this task.

5.1 Accounting for Education Quality

Suppose that one were willing to *assume* that the returns to schooling of immigrants measure a country's education quality. In this case, sectoral heterogeneity is no longer needed, and the model can be simplified as in the previous section. Under this assumption it is possible to integrate education quality into a two step levels accounting exercise. This exercise is an extension of Bils and Klenow (2000) and yields quantitative results similar to those from calibrating the full model.

As in Bils and Klenow, the key parameter is η, which governs diminishing marginal returns to schooling. The first step of the procedure estimates this η. School choice is an endogenous response to education quality differences. Then η is estimated as the parameter that explains observed school choice differences as responses to observed education quality differences. Combining (13) and (16) in logs, relative to the United States, the relevant regression is based on:

$$\log\left(\frac{S_j}{S_{US}}\right) = \frac{\eta}{1-\eta}\log\left(\frac{M_{US}^j}{M_{US}}\right) \tag{18}$$

where $M_{US}^j/M_{US} = Q_j/Q_{US}$.

Table 6 contains the results of the regressions to estimate η. The United States is excluded from all regressions. Column (1) gives the results for estimation by OLS. The estimate returns to schooling of immigrants is small, which implies a small η. Expressing the identification of η as a regression makes clear a likely problem, namely that the education

[17] An alternative approach is to relax the efficiency units assumption and allow workers with different skill levels to be imperfect substitutes. This approach is adopted in Caselli and Coleman (2006) and in a later section of Hendricks (2002), which also finds a larger role for human capital.

Table 6: Elasticity of Schooling With Respect to Education Quality

	OLS	IV			
		HKQL2*	Weighted[a]	PISA	TIMSS
	(1)	(2)	(3)	(4)	(5)
Returns, Imm.	0.366	1.051	0.719	0.671	2.255
	(0.060)	(0.298)	(0.179)	(0.212)	(1.886)
Implied η	0.268	0.512	0.418	0.402	0.690
N	87	69	68	36	41
Income Difference	10.2	3.3	4.3	4.6	2.4
% Accounted For	82%	42%	51%	54%	31%

Standard errors are in parentheses.

[a] Same as Column (2), but weighted by number of immigrants used to estimate returns to schooling in U.S. Mexico is excluded in this case.

quality measures on the right-hand side are noisy. For instance, Tanzania is estimated to have the highest returns, but with only 76 observations. Further, differences in the patterns of selection may explain some of the observed returns, although Section 3.5 argues that differential selection was unlikely to explain the all of the returns-schooling relationship.

Fortunately, test scores on internationally standardized achievement tests offer plausible instruments. They are highly correlated with returns to schooling of immigrants, and should have no role in the main regression except as instruments for education quality. Columns (2) - (5) show the IV regression results, using log-test scores from different testing regimes. The results are much larger in each case. Hanushek-Kimko test scores offer the largest sample, and yield a more plausible estimate of $\eta = 0.512$, Column (2). Column (3) again uses Hanushek-Kimko test scores as instruments, but also weights the results by the number of observations used to estimate the returns to schooling of immigrants; Mexico is excluded since it is one-third of the sample. Columns (4) and (5) give results using the PISA and TIMSS test scores, which offer smaller samples. From these results I infer that $\eta = 0.51$ is a reasonable benchmark. It is estimated on the largest sample, agrees closely with the calibrated value, and as is shown below, suggests conservative results for income differences relative to most of the other regressions.

The second step of the accounting exercise uses the estimated η to construct human capital stocks. It is possible to construct them directly using the human capital production function, equation (6). However, the large difference between OLS and IV estimates of equation (18) suggest that education quality measures are noisy. Hence a preferred alternative is to use workers' first order condition (equation (16)) to substitute out for education quality, yielding:

$$\log(H_j) = \frac{MS_j}{\eta} \tag{19}$$

For now, M is treated as fixed across countries at the sample average level; in the next section I take up the question of variation in returns. The last two columns of Table 6 give the results, in terms of the predicted income difference between the top and bottom quintiles and the fraction of actual income differences accounted for. The benchmark estimate of $\eta = 0.51$ in Column (2) produces conservative income differences compared to other estimates. Quality-adjusted schooling is estimated to account for 42% of income differences, against 40% in the calibration. Hence, the results suggest that assuming returns to schooling of immigrants measure education quality and performing a simple accounting exercise yields similar results as compared to calibration of the full model consistent with all data moments. Finally, note that even the lowest estimate for the role of human capital, 31% in Column (5), is larger than the 21-24% in the previous literature. It is based off of the least precise estimate of η, using the smallest sample.

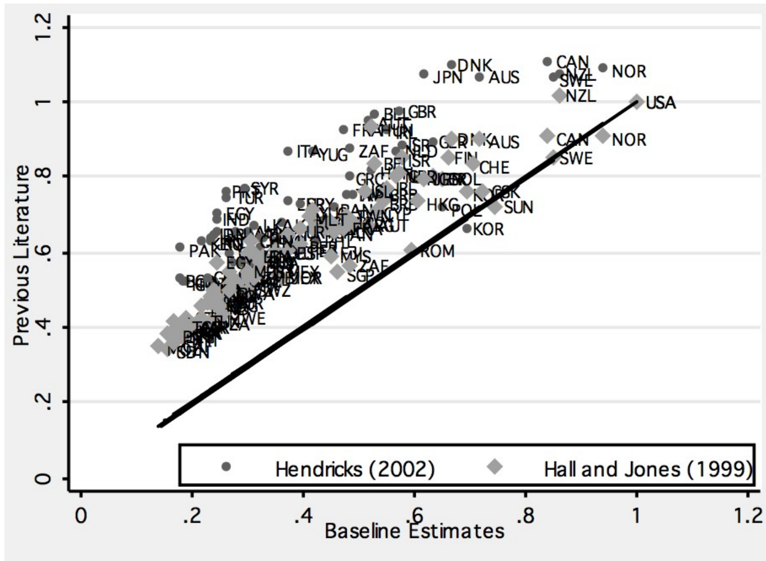
Figure 3 breaks out the country-by-country predictions for human capital per worker, with the benchmark estimates using $\eta = 0.51$ on the x-axis and the Hall and Jones and Hendricks numbers both plotted on the y-axis. If their estimates agreed with this paper's they would lie on the 45-degree line, which is included for reference. Instead for almost all countries in both papers their estimates lie above the 45-degree line, indicating that they estimate smaller human capital differences.

5.2 Differences in Costs and Frictions Across Countries

The key parameter η is calibrated or estimated under the assumption that observed school attainment differences are due to observed education quality differences. In practice, other factors affect schooling and complicate this identification. For instance, the accounting so far has assumed that the relative tuition costs of schooling are the same across countries. Differences in the financial costs of school, such as high subsidies in some developed countries, may also play a role in observed schooling differences.

Additionally, the observed school choices may not be optimal responses to education quality if there are frictions. Two frictions are particularly likely to affect school choices in at least some countries. First, the baseline model requires young workers to finance tu-

Figure 3: Human Capital Relative to U.S.



ition and consumption during schooling years through borrowing or the savings of previous generations. The presence of credit constraints and imperfect altruism would depress attainment below the frictionless level. While a growing literature suggests credit constraints are not important for the United States, there is evidence that they operate in developing countries.[18] In this case, the low attainment of developing countries is due in part to frictions and not low education quality. A second friction more applicable to developed countries is compulsory schooling laws. Recent work by Oreopoulos (2007) suggests that compulsory schooling laws in the United Kingdom raised schooling, so it may be reasonable to question whether the high attainment of developed countries is due in part to frictions and not high education quality.

Both differences in financial costs and differences in frictions affect the model in a similar manner, which is clear in the aggregate production function approach. Denote by S_j^* the optimal schooling level in country j, which would prevail without frictions. In the economy with frictions the actual school attainment is $S_j = \lambda_j S_j^*$, where λ_j measures the quantitative impact of frictions; $\lambda_j < 1$ would correspond to binding credit constraints, while $\lambda_j > 1$ would correspond to compulsory schooling laws. In this case the key estimation equation

[18] See Banerjee and Duflo (2005) for developing countries, and Stinebrickner and Stinebrickner (2008), Carneiro and Heckman (2002), and Cameron and Taber (2004) for the United States.

(equation (18)) is modified to:

$$\log\left(\frac{S_j}{S_{US}}\right) = \log\left(\frac{\lambda_j}{\lambda_{US}}\right) - \frac{1}{1-\eta}\log\left(\frac{1+\mu_j}{1+\mu_{US}}\right) + \frac{\eta}{1-\eta}\log\left(\frac{M^j_{US}}{M_{US}}\right) \tag{20}$$

Regressing equation (20) without accounting for frictions and tuition costs leads to biased estimates of η. The question is how to quantify the role of these hard to measure factors.

Fortunately, costs and frictions both also affect observed Mincerian returns. To see why, first suppose that developing countries face the same costs and frictions as developed countries. In this case, their low average attainment is an optimal response to low education quality; but their Mincerian returns should be the same as those in developed countries. If their low schooling is the result of high costs, and workers equate Mincerian returns to opportunity costs, then Mincerian returns should be higher than in developed countries. If their low schooling is the result of frictions that limit schooling, then attainment is above the efficient level. Given diminishing returns to schooling, Mincerian returns will again be higher than in developed countries. Taking the equivalent of equation (9) for this model yields the formal equation:

$$\log(M_j) = (\eta - 1)\log(\lambda_j) + \log(\rho(1+\mu_j)) \tag{21}$$

Differences in Mincerian returns between developed and developing countries can be used to infer differences in costs and frictions.

Following Bils and Klenow (2000), I regress log Mincerian returns on log average school attainment. The estimated relationship is $\log(\hat{M}_j(S)) = -2.109 - 0.188\log(S_j)$. The standard errors are 0.172 and 0.092, indicating both coefficients are statistically significant at conventional levels. The fitted relationship suggests that in general, countries with higher school attainment have lower returns to schooling and hence lower costs or fewer constraints. Bils and Klenow estimated a much steeper relationship, $\log(\hat{M}_j(S)) = -1.139 - 0.58\log(S_j)$. Their data included several point estimates that have since been identified as potentially noisy, and which were dropped from the Banerjee and Duflo (2005) data used here (see Bennel (1996) for further discussion). Below I show that the main results are also robust to using their estimated relationship.

Integrating the fitted relationship into the estimation of η and the construction of human

Table 7: Robustness to Costs and Frictions

	This Paper	Bils and Klenow (2000)
η	0.416	0.215
% of S Attributed to Q	68%	26%
Income Difference	3.1	4.6
% Accounted For	40%	54%

capital stocks leads to variations on (18) and (19):

$$\log\left(\frac{S_j}{S_{US}}\right) = \frac{\eta}{1-\eta}\log\left(\frac{M_{US}^j}{M_{US}}\right) + \frac{1}{\eta-1}\log\left(\frac{\hat{M}_j(S)}{\hat{M}_{US}(S)}\right)$$

$$\log(H_j) = \frac{S_j}{\eta}\hat{M}_j(S)$$

The first column of Table 7 gives the results of extending the baseline case (Column (2) of Table 6) to account for frictions and costs in this way. η is adjusted downward, reflecting a lower estimate of the elasticity of school attainment in response to education quality. Only 68% of attainment differences are attributed to education quality, with the remaining 32% attributed to differences in costs and frictions. The accounting predicts modestly smaller human capital differences, accounting for 40% instead of 42% in the baseline measure. The estimates are robust to reducing the overall role for education quality in explaining years of schooling differences. The second column shows the results of using the Bils and Klenow estimated relationship between Mincerian returns and schooling. The income results are actually larger. Their fitted curve implies that quality is relatively unimportant, accounting for only a quarter of cross-country school differences. However, their data set features high measured returns to schooling, which inflates the importance of education. Using the previous data thus also implies a larger role for education, albeit through a different channel.

6 Model with Ability Heterogeneity

The baseline model derives implications based on labor markets where sectors but not workers are ex-ante heterogeneous. This section extends the model to allow for ex-ante worker heterogeneity in ability. The key qualitative properties of the model continue to hold. However, worker heterogeneity complicates the interpretation of returns to schooling for both immigrants and non-migrants. One particular question of interest is whether an ability bias in measured returns for non-migrants necessarily lowers the importance of human capital implied by the model.

6.1 Changes to the Model

The most interesting form of heterogeneity is in Q_j, which can represent education quality or cognitive ability heterogeneity. Let d denote the set of different dynasties and $Q_j(d)$ denote the effective education quality of dynasty d. The human capital production function is now given by:

$$H_j(d) = \exp\left[\frac{(S_j(d)Q_j(d))^{\eta}}{\eta}\right] \tag{22}$$

It is convenient to disaggregate effective education quality as $Q_j(d) = \bar{Q}_j(1+\tilde{Q}_j(d))$, where $\bar{Q}_j$ is country j's average education quality and $\tilde{Q}_j(d)$ is the dynasty's mean 0 idiosyncratic cognitive ability component. Differences in $\tilde{Q}_j(d)$ lead to differences in the rate of human capital formation per year of schooling in the population.

Otherwise, the production side, Euler equations, and income maximization decisions are all as in Section 2. Individual workers still go to school until marginal costs and marginal benefits are equated:

$$\frac{\partial \log(W_j(S, Q, \gamma))}{\partial S} = \rho(1 + \mu_j)$$

However, ability heterogeneity biases measured Mincerian returns. It may be helpful to think of price-taking firms in each sector posting competitive wages $W_j(H, \gamma)$. On the balanced growth path, workers can perfectly forecast these wages. They choose a sector of employment $\gamma_j(d)$ and how long to go to school $S_j(d)$. Their optimal schooling level given their choice of $\gamma_j(d)$ is:

$$S_j(d) = \left[\frac{\gamma_j(d)\,(Q_j(d))^{\eta}}{\rho(1 + \mu_j)}\right]^{1/(1-\eta)} \tag{23}$$

Since ability and skill intensity are complementary, higher-ability workers work in more skill-intensive sectors and obtain more schooling. Then cross-sectional Mincerian returns overstate the private returns to schooling. As long as the distributions of workers (across abilities) and sectors (across skill intensities) are continuous and well-behaved, observed Mincerian returns are given by[19]:

$$
\begin{aligned}
M_j &= \frac{\frac{\partial \log(W)}{\partial S} S'(Q) + \frac{\partial \log(W)}{\partial \gamma}\gamma'(Q) + \frac{\partial log(W)}{\partial Q}}{S'(Q)} \\
&= \rho(1+\mu_j)\left(1 + \frac{1-\eta}{\eta + \varepsilon_{\gamma,Q}}\right)
\end{aligned}
$$

The size of the bias in Mincerian returns depends on the elasticity of sector of employment with respect to ability, $\varepsilon_{\gamma,Q}$, which is an equilibrium object in the model. Two special cases illustrate the bias in observed returns. If there is no ability heterogeneity, then in the limit $\varepsilon_{\gamma,Q} = \infty$. In this case all the observed schooling heterogeneity is driven by sectoral heterogeneity, and the observed returns are an unbiased estimate of private returns, $M_j = \rho(1+\mu_j)$, as in the previous model. If there is no sectoral heterogeneity, then in the limit $\varepsilon_{\gamma,Q} = 0$. In this case all the observed schooling heterogeneity is driven by ability heterogeneity, and the observed returns are biased upward by a constant proportion of private returns, η^{-1}. The calibrated equilibrium falls in between these two extremes, with an intermediate bias in Mincerian returns.

Immigrants are still assumed to earn the same wages as Americans with the same human capital. Taking the local derivative of their wage expression yields:

$$
M_j^i = \frac{Q_i(d)}{Q_j(d)} M_j = \left(\frac{\bar{Q}_i}{\bar{Q}_j}\right)\left(\frac{1+\tilde{Q}_i(d)}{1+\tilde{Q}_j(d)}\right) M_j \ |_{H_j(d)=H_i(d)} \tag{24}
$$

The returns to schooling of immigrants are determined by relative education quality, as well as their cognitive ability relative to the American worker with the same human capital. These equations summarize the two novel predictions of the model with ability heterogeneity: observed returns overstate private returns; and returns to schooling for immigrants are systematically biased by immigrant selection. The next section discusses the impact of the second bias on the results.

[19]The first line is the total change in wages from a marginal change in cognitive ability, divided by the total change in schooling from a marginal change in cognitive ability. This local change is exactly the interpretation of Mincerian returns with cognitive ability heterogeneity. Continuity ensures that $\frac{\partial \log(W)}{\partial \gamma} = 0$ by the envelope theorem. The rest of the second line follows from the firm's first-order conditions.

Table 8: Education of Representative Quintiles

	Quintile					
Observation	1	2	3	4	5	U.S.
Schooling	3.03	5.34	6.25	8.05	9.65	12.2
Immigrant Schooling	12.8	11.5	11.8	12.3	14.2	13.5

Other values are as given in Table 3.

6.2 Selection on Education

Immigrants to the United States are overwhelmingly more educated than non-migrants born in the same country. Data on average years of schooling is available from Barro and Lee (2001) for 78 of the 130 countries in the sample in Section 3. For every country except Mexico, immigrants have more schooling than non-migrants. In some cases, the selection is quite extreme: immigrants from Afghanistan, Nepal, Sierra Leone, and Sudan all have 13-14 years of schooling, while non-migrants in those countries have 1-2 years of schooling. The average country's immigrants are nearly twice as educated as its non-migrants. Hence selection is large on average, and varies across countries.[20] Table 8 reduces this information to the representative quintiles. The first line gives the average attainment for non-migrants, repeated from Table 3. The second gives the average attainment for immigrants, taken from the sample of Section 3. Immigrants from developing countries are much more selected on education.

According to equation (23), immigrants who are strongly selected on education should also be strongly selected on ability. Since ability heterogeneity is the only dimension of worker heterogeneity, the calibrated model has a one-to-one mapping $S(\tilde{Q})$. This mapping can be inverted to determine the degree of ability selection, given the observed degree of selection on schooling. Since immigrants are generally positively selected on education, they are inferred to be positively selected on ability. Since immigrants from developing countries are more selected on education, they are inferred to be even more selected on ability.

Incorporating ability heterogeneity then has two opposing effects on the results. First, Mincerian returns overstate private returns. Adjusting down the private return to schooling leads to a lower role for quality-adjusted schooling in accounting for cross-country income

[20]There is also a slight discontinuity since the Section 3 data measures average schooling among workers, while the Barro-Lee data is average schooling in the population over 25. Hence, the average American in my sample has 13.5 years of schooling, while Barro-Lee report an American average of 12.2, indicating that Americans are "selected" by 1.3 years. Still, only Mexican immigrants are less selected.

differences. Second, immigrants from developing countries are more selected on schooling, so more selected on ability. Widening the gap in education quality between developed and developing countries tends to increase the role of quality-adjusted schooling in accounting for cross-country income differences. It is necessary to re-calibrate the model to quantify these effects.

6.3 Calibration

Calibration begins with the same parameters and moments as the baseline calibration of Section 4. In addition, it is necessary to specify a distribution for cognitive ability. As was shown earlier, this distribution implicitly determines the size of the ability bias in Mincerian returns. Card (2001) surveyed the results from the labor literature of OLS and IV estimates of the returns to schooling. His findings suggest that a plausible upper bound would attribute 10% of measured returns to ability bias. To give the ability bias story the largest chance, I pick the ability distribution in each country so that 10% of measured returns at every level of schooling are due to ability bias (i.e., 0.93% of the observed average 9.3% returns). The ability distribution is also chosen to have a mean of 1, but the shape of the distribution that satisfies these conditions varies somewhat across countries.

The second change to the calibration procedure is that the returns to schooling of immigrants to the United States are no longer a valid measure of their source country education quality, because immigrants may be selected. Hence, it is no longer appropriate to treat M_j^i as a direct observation on $\bar{Q}_i$. Instead, I add $\bar{Q}_i$ to the set of parameters to be calibrated, and M_j^i to the set of moments to be matched. For each country j I simulate the entire distribution of outcomes. I find the immigrant for whom $S_j(\tilde{Q}_j)$ is the same as the average S_j for immigrants in Table 8. I then simulate the measured returns using equation (24).

As before, the parameters α, δ, ρ, and g are calibrated to outside evidence. The parameters μ, η, ψ, and $\bar{\gamma}$ are recalibrated to fit the same moments. Five new parameters, Q_j for the five quintiles, are calibrated to fit the observed returns to schooling for immigrants, given the implied degree of selection. Table 9 gives the re-calibrated parameters; those chosen based on outside evidence are the same as in the previous calibration and are not presented.

Of the key parameters, the tuition cost of education and the elasticity cost of schooling are now lower than in the baseline calibration. Both changes point towards a lower role for quality-adjusted education. However, the model also adjusts the role for education quality. In the table, these figures are given in terms of calibrated degree of selection for

Table 9: Alternative Model Calibrated Parameters

Parameter	Role	Value
μ	Average Mincerian Return, Quintiles 1-5	0.66
η	Elasticity of Schooling w.r.t. Quality, Quintiles 1-5	0.45
$\underline{\gamma}$	Coefficient of Variation in Schooling, U.S.	0.52
$\bar{\gamma}$	Coefficient of Variation in Schooling, U.S.	1.48
ψ	Within-Industry Educational Differences, U.S. - Quintile 1	8.4
$\tilde{Q}_1$	Returns to Schooling, Quintile 1 Immigrants	13%
$\tilde{Q}_2$	Returns to Schooling, Quintile 2 Immigrants	9%
$\tilde{Q}_3$	Returns to Schooling, Quintile 3 Immigrants	10%
$\tilde{Q}_4$	Returns to Schooling, Quintile 4 Immigrants	5%
$\tilde{Q}_5$	Returns to Schooling, Quintile 5 Immigrants	1%

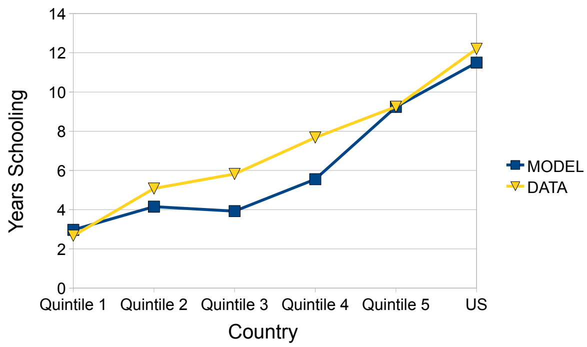
the five quintiles; for instance, immigrants from Quintile 1 are calibrated to have 13% higher cognitive ability than the average non-migrant. Immigrants from Quintile 1 are 12% more selected than immigrants from Quintile 5. This selection affects observed returns: the calibration implies that 24% of the already low returns for Quintile 1 immigrants were due to selection, while only 4% of the returns for Quintile 5 immigrants were due to selection. The next section gives the results and decomposes these competing effects.

6.4 Results

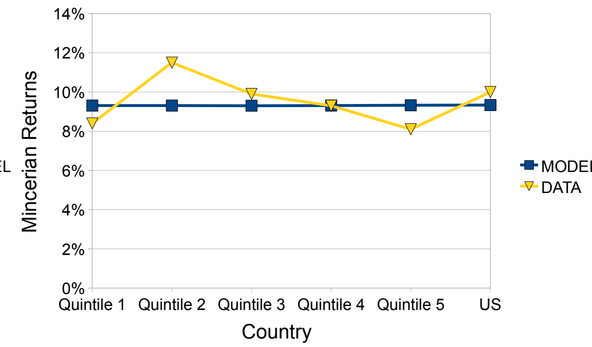
Figure 4 gives the model's fit in terms of average school attainment and Mincerian returns for the five quintiles. The fit is nearly indistinguishable from that of the baseline model. As before, the μ_j could be used as separate parameters to fit either the Mincerian returns or the average attainment by country better, but not both.

Given that the model again quantitatively replicates the data, I back out the implied importance of quality-adjusted schooling in accounting for cross-country income differences. The results are given in Table 10. The data and baseline model results are given in the first two rows. The results from the calibrated model with ability heterogeneity are given in the third row. Accounting for ability lowers the model's predicted income differences across quintiles from 3.11 to 2.69, and lowers the fraction of income differences explained from 40% to 35%.

The ability model generates different results through three channels: accounting for the bias in Mincerian returns, accounting for the bias in returns to schooling for immigrants, and changes in other parameters such as η. To decompose these effects, I turn to the



(a) Predicted vs. Actual S_j



(b) Predicted vs. Actual M_{US}^j

Figure 4: Calibrated Model with Heterogeneity vs. Data

Table 10: Income Differences Due to Schooling

	Income Ratio	% Accounted For
Data	17.2	100%
Ability Model, One Good Interpretation	3.11	40%
New Model, One Good Interpretation	2.69	35%
Experiment 1: Only Returns Bias	2.73	35%
Experiment 2: Only Selection	3.44	44%
Experiment 3: Returns and Selection	3.05	39%

baseline model without ability heterogeneity. I consider three changes to the calibration targets of this model, designed to decompose the three channels above. The first experiment calibrates μ to fit a Mincerian return equal to 90% of the observed level, isolating the impact of the ability bias on measured returns. The rest of the parameters are re-calibrated to the same targets as in Section 4. The results are modestly lower, accounting for only 35% of income differences instead of 40%. In the second experiment the Q_j are replaced with the selection-adjusted Q_j implied by Table 9, which lowers education quality most in developing countries. The results of this experiment are modestly higher, accounting for 44% of income differences. These two effects would seem to offset. The third experiment confirms that they nearly do. It calibrates μ and takes the selection-adjusted Q_j, combining the first two experiments. The combined impact of these two forces is that quality-adjusted schooling accounts for 39% of income differences, almost exactly the same result as for the model without ability heterogeneity.

These experiments indicate that ability heterogeneity introduces two nearly offsetting biases into the accounting exercise. The calibrated model with ability heterogeneity finds lower results because it also changes other parameters, notably calibrating a lower value of η. The lowest estimated role for quality-adjusted schooling is 35%, still a much larger effect than the previous literature.

7 Conclusion

This paper develops a model of labor markets where education quality varies exogenously across countries. Education quality differences are measured using the returns to schooling of immigrants to the United States. The implied education quality differences are large, as much as an order of magnitude between developed and developing countries. Differences in education quality may be the cause of cross-country schooling differences, since high education quality and high returns provide students with incentives to stay in school. The model suggests that quality-adjusted schooling accounts for a factor of around 3 of the income difference between the richest and poorest quintiles of countries, or around 40% of the observed income differences. The results account for an extra 15% of the observed income differences as compared to accounting for years of schooling alone, as in Hall and Jones (1999).

Policy advocates often suggest an expansion of education in developing countries as one way to increase income per capita. This paper offers mixed conclusions on the efficacy of such a policy. On the one hand, quality-adjusted schooling does account for a large fraction of cross-country income differences. On the other hand, education quality plays a large role in this conclusion, accounting for almost as much of income differences as education quantity. Most proposed experiments expand quantity through compulsory school laws, building additional schools, and so on. The estimates of η here (approximately 0.4 to 0.5) imply steep diminishing returns to schooling conditional on quality, rendering an expansion of years of schooling of questionable value. For example, doubling the attainment in the poorest quintile (from 2.67 to 5.34 years) would increase output per capita by just 25-29% and lower Mincerian returns by 32-42%. The value of such an expansion is smaller than earlier studies. Given limited budgets, an increase in quantity may be implemented through a decline in quality, further complicating the tradeoff.

By design, this paper has nothing to say about the sources of education quality differences. Hence, it is not appropriate to offer policy advice about improving education quality.

Rather, it is hoped that these estimates will provide useful evidence for future work.

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A Model Details

A.1 Market Clearing Conditions

There are market clearing conditions in this model for the final goods market, the capital market, the intermediate goods market for each good, and the labor market for each schooling level. For convenience, let d index the continuum of dynasties. Then the market clearing conditions are given by:

$$Y_j(t) = \int_0^1 \left[C_j(d,t) + \dot{K}_j(d,t) + \delta K_j(d,t)\right] dd \ \forall j, t \tag{25}$$

$$\int_{\underline{\gamma}}^{\bar{\gamma}} K_j(\gamma,t) d\gamma = \int_0^1 K_j(d,t) dd \ \forall t \tag{26}$$

$$X_j(\gamma,t) = Y_j(\gamma,t) \ \forall j, t, \gamma \tag{27}$$

$$L_j(\gamma,t) = \int_0^1 I\left(S_j(d) = S_j(\gamma)\right) \frac{T_j - S_j(d)}{T_j} dd \ \forall j, t, \gamma \tag{28}$$

$I(S_j(d) = S_j(\gamma))$ is an indicator function. Then the first three market clearing conditions are entirely standard. The fourth requires that in equilibrium, the employment of industry γ equals the fraction of workers who have the appropriate level of schooling, $I(S_j(d) = S_j(\gamma))$, times the labor supply of those workers, $\frac{T_j - S_j(\gamma,t)}{T_j}$.

A.2 Definition of Equilibrium

An equilibrium consists of prices $(R_j(t), W_j(S,t), P_j(\gamma,t))_{t\in[0,\infty)}$ and allocations for intermediate industries
$(K_j(\gamma,t), L_j(\gamma,t), Y_j(\gamma,t), S_j(\gamma,t))_{t\in[0,\infty)}$, for the final goods producer $(X_j(\gamma,t), Y_j(t))_{t\in[0,\infty)}$, and for the dynasties $(K_j(d,t), C_j(d,t) S_j(d,t))_{t\in[0,\infty)}$, for each country j. These variables must satisfy four conditions:

1. Taking prices as given, workers maximize (1) subject to (2) and (3).

2. Taking prices as given, intermediate producers maximize (7).

3. Taking prices as given, the final goods producer maximizes (10).

4. The market clearing conditions, (25)-(28).

A balanced growth path is an equilibrium such that the variables $R_j, P_j(\gamma), L_j, L_j(\gamma), S_j(\gamma)$,and $S_j(d)$ are constant, while $W_j(S,t), K_j(\gamma,t), Y_j(t), Y_j(\gamma,t), X_j(\gamma,t), K_j(d,t)$, and $C_j(d,t)$ grow at the same rate g as technology.

B Country Quality Estimates

Table 11: Quality Estimates

Country	Obs	Returns	S.E.
Tonga	111	-0.013	0.060
Albania	349	-0.010	0.032
Macedonia, FYR	147	-0.004	0.047
Kosovo	43	-0.004	0.070
Nepal	89	0.001	0.057
Lao PDR	1633	0.004	0.010
Somalia	178	0.004	0.031
Serbia	86	0.004	0.054
Sierra Leone	220	0.004	0.054
Bosnia and Herzegovina	1163	0.006	0.021
Guatemala	5146	0.007	0.007
Honduras	2829	0.008	0.010
Cambodia	1071	0.008	0.013
Cape Verde	292	0.008	0.030
Mexico	78575	0.009	0.002
El Salvador	8519	0.009	0.006
Sudan	118	0.010	0.052
Azores	195	0.010	0.043
Eritrea	152	0.013	0.045
Ecuador	2461	0.013	0.011
Dominican Republic	5075	0.014	0.007
Armenia	321	0.015	0.034
Bolivia	432	0.018	0.034
Samoa	90	0.018	0.055
Iraq	600	0.019	0.019
Yugoslavia	559	0.019	0.023
Korea, Rep.	653	0.019	0.026
Portugal	1666	0.019	0.013
Vietnam	8922	0.020	0.005
Cuba	6091	0.021	0.008
Liberia	351	0.023	0.040

Continued on Next Page

Table 11: Quality Estimates

Country	Obs	Returns	S.E.
Uganda	108	0.023	0.067
Nicaragua	1905	0.024	0.012
Costa Rica	520	0.024	0.023
Belize	253	0.024	0.040
Colombia	4116	0.025	0.008
Peru	2679	0.027	0.013
Thailand	877	0.027	0.017
Haiti	4329	0.027	0.009
Antigua and Barbuda	138	0.028	0.068
Barbados	470	0.029	0.035
Jordan	191	0.029	0.046
Ethiopia	581	0.029	0.030
Poland	3929	0.030	0.011
Yemen, Rep.	102	0.031	0.041
Syrian Arab Republic	308	0.031	0.028
Bangladesh	632	0.032	0.021
Uzbekistan	162	0.032	0.064
Saudi Arabia	64	0.032	0.089
Grenada	226	0.034	0.046
Dominica	142	0.036	0.058
Senegal	90	0.036	0.051
Puerto Rico	5530	0.038	0.007
Croatia	277	0.039	0.036
Italy	1720	0.039	0.011
Greece	728	0.040	0.021
Bahamas, The	128	0.041	0.068
Nigeria	1080	0.042	0.021
Paraguay	66	0.042	0.076
Ghana	748	0.042	0.027
Myanmar	352	0.044	0.026
Czech Republic	114	0.046	0.079
Spain	516	0.046	0.022
Czechoslovakia	160	0.047	0.057
Brazil	1716	0.047	0.014
Turkey	459	0.047	0.025
Pakistan	1390	0.047	0.015
Romania	1158	0.048	0.019
Bulgaria	313	0.048	0.041

Continued on Next Page

Table 11: Quality Estimates

Country	Obs	Returns	S.E.
Trinidad and Tobago	1617	0.048	0.018
Austria	159	0.049	0.049
Afghanistan	226	0.050	0.038
Moldova	175	0.050	0.057
Venezuela, RB	633	0.051	0.023
Algeria	89	0.051	0.058
Philippines	13581	0.053	0.006
Cyprus	43	0.053	0.079
Fiji	321	0.054	0.035
Latvia	97	0.054	0.084
Jamaica	5192	0.054	0.010
Morocco	267	0.054	0.038
Guyana	2074	0.054	0.014
Chile	611	0.055	0.025
Ukraine	2065	0.056	0.016
Finland	131	0.057	0.067
Indonesia	402	0.057	0.035
St. Lucia	117	0.057	0.075
Egypt, Arab Rep.	781	0.057	0.026
Cameroon	77	0.058	0.088
Kenya	264	0.058	0.047
Azerbaijan	134	0.059	0.059
Uruguay	213	0.059	0.046
China	8726	0.060	0.005
Georgia	71	0.060	0.080
Lebanon	481	0.061	0.026
Panama	632	0.061	0.030
Belarus	327	0.061	0.046
Argentina	884	0.063	0.020
Sri Lanka	262	0.065	0.042
St. Vincent and the Grenadines	168	0.065	0.046
Iran, Islamic Rep.	1468	0.065	0.019
Taiwan	1670	0.066	0.017
India	6669	0.067	0.007
Denmark	159	0.069	0.056
St. Kitts and Nevis	100	0.071	0.101
Ireland	772	0.072	0.029
Lithuania	115	0.074	0.079

Continued on Next Page

Table 11: Quality Estimates

Country	Obs	Returns	S.E.
Israel	585	0.075	0.026
France	719	0.077	0.024
Singapore	116	0.078	0.063
Hong Kong, China	1198	0.079	0.016
Malaysia	325	0.080	0.029
Australia	477	0.080	0.040
Germany	2773	0.082	0.014
Bermuda	62	0.083	0.088
Kuwait	43	0.084	0.095
Canada	4183	0.087	0.012
Hungary	316	0.089	0.038
Zimbabwe	95	0.089	0.089
Slovak Republic	105	0.090	0.089
New Zealand	203	0.091	0.059
United States	4300000	0.092	0.000
Netherlands	364	0.095	0.039
Switzerland	210	0.098	0.057
Belgium	134	0.098	0.053
South Africa	525	0.098	0.036
United Kingdom	4485	0.098	0.013
Norway	127	0.104	0.071
Japan	2345	0.106	0.016
Sweden	237	0.114	0.054
Tanzania	76	0.127	0.095

Note: Country is the country name as it is recorded in the Census files. Obs is the number of observations in the 2000 5% PUMS meeting the sample restrictions. Returns are the log-wage returns to schooling. The returns are measured in percentage points. S.E. is the standard error of the returns.